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PARAMETRIC OPTIMIZATION OF POWDER EDM PROCESS USING GREY RELATIONAL ANALYSIS AND TOPSIS

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ABSTRACT

There are strong needs for productive/quality machining strategies of notoriously “difficult-to-machine” aerospace materials, automobile parts, surgical instruments and super alloys. The newest EDM technology may be able to machine intricate and complex 3D structures and also circumvent the problems encountered in mechanical machining methods. This study is based on parametric optimization of powder-mixed EDM machining of EN-31 tool steel. Copper is used as micro-tool. GRA and TOPSIS are used for optimization of parameters. The optimum parametric conditions were found to be 150µs/0.7DC/12A/2g/l. Peak current (I_p) was found to be the most influencing factor followed by conc (D) then time-on-pulse (T_{on})and finally duty cycle DC. It is also observed that with powder-mixed dielectrics. MRR was found to be high and R_a to be low. Moreover, the machined surface develops high resistance to corrosion and abrasion.

KEYWORDS: Grey Relational Analysis, Electro Discharge Machining

INTRODUCTION

Electro Discharge Machining is one of the advanced machining process where the material removal occurs by melting and vaporization due to the thermal energy produced between the work piece and the electrode. All electrically conductive material can be machined by EDM. Powder mixed EDM (PMEDM) has a different machining mechanism from the conventional EDM [1]. In this process, a suitable material in the powder form is mixed into the dielectric fluid either in the same tank or in a separate tank. For better circulation of the powder mixed dielectric, a stirring system is employed. For constant reuse of powder in the dielectric fluid, a modified circulation system is used. The experimental setup consists of a transparent bath like container, called machining tank. It is placed in the work tank of EDM and the machining is performed in this container. To hold the work piece, a work piece fixture assembly is placed in it. The machining tank is filled up with dielectric fluid. To avoid particle settling, a stirring system is incorporated. A small dielectric circulation pump is used for proper circulation of the powder mixed dielectric fluid into the discharge gap. The pump and the stirrer assembly are placed in the same tank in which machining is performed. The distance between powder mixed dielectric suction point and nozzle outlet is kept as short as possible (10 in.) in order to ensure the complete suspension of powder in the discharge gap. Magnetic forces were used to separate the debris from the dielectric fluid. For this purpose, two permanent magnets areplaced at the bottom of machining tank. The various powders that can be added into the dielectric fluid are aluminum, chromium, graphite, silicon, copper or silicon carbide, etc. The spark gap is filled up with powder particles. When voltage is applied the powder particles get energized and behave in a zigzag fashion [2]. These charged particles are accelerated by the electric field and act as conductors.

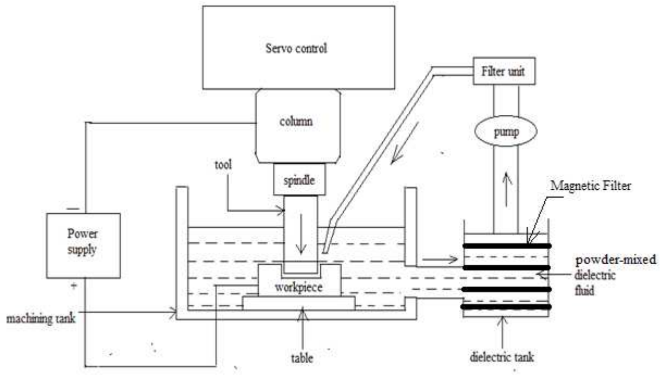


Figure 1: PMEDM Set-Up

The conductive particles promote breakdown in the gap and increase the spark gap between tool and the workpiece. Under the sparking area, the particles come close to each other and arrange themselves in the form of chain like strutures between both the electrodes. The interlocking between the different powder particles occurs in the direction of flow of current. The chain formation helps in bridging the discharge gap between both the electrodes. Due to *bridging effect*, the insulating strength of the dielectric fluid decreases. The easy short circuit takes place, which causes early explosion in the gap. As a result, a '*series discharge*' starts under the electrode area. The faster sparking within a discharge takes place causing faster erosion from the workpiece surface and hence the material removal rate (MRR) increases. At the same time, the added powder modifies the plasma channel. The plasma channel becomes enlarged and widened [3]. The sparking is uniformly distributed among the powder particles, hence electric density of the spark decreases. Due to uniform distribution of sparking among the powder particles, shallow craters are produced on the workpiece surface. This results in improvement in surface finish[4].In this process, an appropriate kind of powder is mixed into the dielectric fluid when a voltage of 80–320 V is applied to both the electrodes; an electric field in the range of 10^5–10^7 V/m is created. The spark gap is filled up with additive particles and the gap distance between tool and workpiece increased from 25–50 μm to 50–150 μm [5].

EXPERIMENTAL DESIGN AND DATA COLLECTION

This study is based on secondary data provided from the research done by **H.K. Kansal, Sehijpal Singh, P. Kumar [6]**. They optimized the process parameters of powder mixed electrical discharge machining (PMEDM). Response surface methodology (RSM) was used to plan and analyze the experiments. The process was studied with a standard RSM design called central composite design (CCD). A total of 30 experiments were conducted at the stipulated conditions. In this design, the factorial design is full factorial design with all combinations of the factors at the two levels

Machining Conditions

The machining conditions are given in Table 1.

Table 1: Machining Conditions

Conditions	Descriptions
Workpiece (+)	EN-31 tool steel
Electrode (−)	Copper microtool, 25mm diameter
Dielectric fluid	Kerosene.
Powder	Silicon (Si)
Powder size (µm)	20-30 µm
Peak current (A)	3-12
Pulse-on-time (µs)	50-150
Duty factor (%)	0.7-0.9

Experimental Matrix and Results for the PEDM Performance Characteristics

Table 2: Design of Experimental Matrix [6]

Expt No	Process Parameters			
	Pulse on Time, T_{on} (µs)	Duty Cycle DC	Peak Current I_p (A)	Concentration D (g/l)
1	50	0.7	3	0
2	150	0.7	3	0
3	50	0.9	3	0
4	150	0.9	3	0
5	50	0.7	12	0
6	150	0.7	12	0
7	50	0.9	12	0
8	150	0.9	12	0
9	50	0.7	3	2
10	150	0.7	3	2
11	50	0.9	3	2
12	150	0.9	3	2
13	50	0.7	12	2
14	150	0.7	12	2
15	50	0.9	12	2
16	150	0.9	12	2
17	50	0.8	7.5	1
18	150	0.8	7.5	1
19	100	0.7	7.5	1
20	100	0.9	7.5	1
21	100	0.8	3	1
22	100	0.8	12	1
23	100	0.8	7.5	0
24	100	0.8	7.5	2
25	100	0.8	7.5	1
26	100	0.8	7.5	1
27	100	0.8	7.5	1
28	100	0.8	7.5	1
29	100	0.8	7.5	1
30	100	0.8	7.5	1

The ranges of these parameters were selected on the basis of preliminary experiments conducted by using one variable at a time approach. Table 3gives the levels of various parameters and their designation. The response parameter in the present study was MRR and surface roughness (SR). In each test, the MRR was calculated by the weight loss method. The SR was measured in terms of arithmetic mean roughness of the evaluated roughness profile (*R*a in µm) by using a Surfcoder SE1200 surface testing analyzer.

Table 3: Design Scheme of Process Parameters and Their Levels [6]

Factor Symbol	Parameter	Levels	
		Low (−1)	High (+1)
A	Pulse on time, T_{on} (μs)	50	150
B	Duty cycle, DC	0.7	0.9
C	Peak current, I_p (A)	3	12
D	Concentration, Conc. (g/l)	0	2

Table 4: Experimental Matrix with Process Parameters and Their Levels

Expt No	Process Parameters			
	Pulse on Time, T_{on} (μs)	Duty Cycle DC	Peak Current I_p (A)	Concentration D (g/l)
1	1	1	1	1
2	3	1	1	1
3	1	3	1	1
4	3	3	1	1
5	1	1	3	1
6	3	1	3	1
7	1	3	3	1
8	3	3	3	1
9	1	1	1	3
10	3	1	1	3
11	1	3	1	3
12	3	3	1	3
13	1	1	3	3
14	3	1	3	3
15	1	3	3	3
16	3	3	3	3
17	1	2	2	2
18	3	2	2	2
19	2	1	2	2
20	2	3	2	2
21	2	2	1	2
22	2	2	3	2
23	2	2	2	1
24	2	2	2	3
25	2	2	2	2
26	2	2	2	2
27	2	2	2	2
28	2	2	2	2
29	2	2	2	2
30	2	2	2	2

Table 5: Observed Values of Output Responses [6]

MRR(mm^3/min)			R_a(μm)		
I	II	Average	I	II	Average
1.84	2.22	2.03	2.48	1.96	2.22
1.98	2.84	2.41	1.98	2.30	2.14
2.19	2.00	2.10	2.30	2.33	2.32
2.88	1.94	2.41	2.41	1.88	2.14
22.30	23.10	22.70	7.21	6.42	6.82
23.41	24.20	23.81	6.14	9.36	7.75
21.65	23.70	22.68	6.50	8.91	7.70

Table 5: Contd.,

24.21	25.20	24.71	6.36	7.13	6.75
3.17	3.17	3.17	2.11	2.34	2.22
3.30	3.47	3.38	1.21	1.48	1.34
3.16	3.24	3.20	4.68	3.54	4.11
3.19	3.56	3.38	1.31	1.37	1.34
26.98	25.21	26.10	5.5	5.48	5.50
28.38	29.44	28.91	6.19	4.05	5.12
26.00	26.39	26.19	6.40	3.84	5.12
28.21	29.20	28.71	5.00	5.23	5.12
4.75	4.63	4.69	3.55	7.81	5.68
8.20	6.19	7.19	7.39	6.51	6.95
7.19	5.20	6.21	6.00	6.02	6.01
7.43	7.14	7.29	7.32	5.47	6.40
2.10	1.95	2.03	1.71	1.89	1.80
25.50	24.52	25.01	6.91	5.06	5.99
5.20	7.19	6.21	7.55	6.07	6.81
6.94	7.65	7.29	4.20	5.36	4.78
6.18	6.21	6.19	7.32	5.47	6.39
6.70	7.28	6.99	6.30	7.30	6.80
6.22	8.09	7.15	6.51	7.09	6.80
7.93	6.59	7.26	6.30	6.09	6.19
6.61	7.15	6.88	6.75	5.55	6.15
7.58	6.82	7.20	5.11	6.85	5.98

Grey Relational Analysis

The grey relational analysis (GRA) is one of the powerful and effective soft-tool to analyze various processes having multiple performance characteristics. Generally, GRA is carried out for solving complicated problems which have interrelationships among the designated performance characteristics[7].

Normalization of the Experimental Results in GRA

Normalization is the process in which transformation of input data takes place to an evenly distributed data in a scale range between 0 and 1. The experimental results for the responses i.e. MRR and Ra are normalized using equations (1)-(2) where x_{ij} is the normalized value of y_{ij}f or response j (j = 1,2,3,….,n) of experiment I (i = 1,2,3,…,m) [8].

If the response is of higher-the-better type, then

$$x_{ij} = \left(y_{ij} - \min\left(y_{ij}\right)\right) / \left(\max\left(y_{ij}\right) - \min\left(y_{ij}\right)\right) \tag{1}$$

If the response is of smaller-the-better type, then normalized value x_{ij} is expressed as

$$x_{ij} = \left(\max\left(y_{ij}\right) - y_{ij}\right) / \left(\max\left(y_{ij}\right) - \min\left(y_{ij}\right)\right) \tag{2}$$

If the normalized value x_{ij} for a response j of experiment i is equal to 1 or nearer to 1, then it is said that the performance of that particular experiment i is best for the response j. That normalized value is termed as reference value (x_{0j}) for jth response [9].

In the present research study, MRR, is of higher-the-better type response whereas Ra is smaller-the-better type response.

Table 6: Normalization Values of Results

Expt. No	MRR(mm^3/min) X_{ij}	R_a(μm) X_{ij}
1	0	0.862715
2	0.014136905	0.875195
3	0.002604167	0.847114
4	0.014136905	0.875195
5	0.768973214	0.145086
6	0.810267857	0
7	0.768229167	0.0078
8	0.84375	0.156006
9	0.042410714	0.862715
10	0.050223214	1
11	0.043526786	0.567863
12	0.050223214	1
13	0.89546131	0.351014
14	1	0.410296
15	0.898809524	0.410296
16	0.992559524	0.410296
17	0.098958333	0.322933
18	0.191964286	0.124805
19	0.155505952	0.271451
20	0.195684524	0.210608
21	0	0.928237
22	0.854910714	0.274571
23	0.155505952	0.146646
24	0.195684524	0.463339
25	0.154761905	0.212168
26	0.18452381	0.148206
27	0.19047619	0.148206
28	0.194568452	0.24337
29	0.180431548	0.24961
30	0.19233631	0.276131

Table 7: Deviation from Ideal Sequence of Ideal Solution

Sl. No	Deviation of MRR ($1-X_{ij}$)	Deviation of R_a ($1-X_{ij}$)
1	1	0.137285
2	0.985863	0.124805
3	0.997396	0.152886
4	0.985863	0.124805
5	0.231027	0.854914
6	0.189732	1
7	0.231771	0.9922
8	0.15625	0.843994
9	0.957589	0.137285
10	0.949777	0
11	0.956473	0.432137
12	0.949777	0
13	0.104539	0.648986
14	0	0.589704
15	0.10119	0.589704
16	0.00744	0.589704
18	0.808036	0.875195
19	0.844494	0.728549
20	0.804315	0.789392

Table 7: Contd.,

21	1	0.071763
22	0.145089	0.725429
23	0.844494	0.853354
24	0.804315	0.536661
25	0.845238	0.787832
26	0.815476	0.851794
27	0.809524	0.851794
28	0.805432	0.75663
29	0.819568	0.75039
30	0.807664	0.723869

Grey Relational Coefficient

The grey relational coefficient is calculated to determine the closeness of x_{ij} to x_{0j}. Higher value of grey relational coefficient means x_{ij} is closer to x_{0j}. Grey relational coefficient is calculated based on equation (3) [8].

$$\gamma\left(x_{0j}, x_{ij}\right) = \left(\Delta_{\min} + \xi\Delta_{\max}\right) / \left(\Delta_{ij} + \xi\Delta_{\max}\right) \text{ for i = 1,2,3,…..,m and j = 1,2,3,….,n} \quad (3)$$

where, $\Delta_{ij} = \left|x_{0j} - x_{ij}\right|$

$$\Delta_{\min} = \min\left\{\Delta_{ij}, i = 1,2,3,....,m; \quad j = 1,2,3,....,n\right\}$$

$$\Delta_{\max} = \max\left\{\Delta_{ij}, i = 1,2,3,....,m; \quad j = 1,2,3,....,n\right\}$$

□ = distinguishing coefficient, i□(0,1)

The normalized values of each of the responses for all 30 experiments are used to calculate the grey relational coefficient using equation (3). The distinguishing coefficient □ is taken as 0.5.

Grey Relational Grade

Grey relational grade is the weighted sum of the grey relational coefficients for a particular experiment and it is calculated using equation (4) [9].

$$\Gamma\left(X_0, X_i\right) = \sum_{j=1}^{n} wj \cdot \gamma\left(x_{0j}, x_{ij}\right) \text{ for } i = 1,2,3,...,m \text{ and } j = 1,2,3,….,n \quad (4)$$

where, *□(X0, Xi)* is grey relational grade between comparability sequence X_i and reference sequence X_0 and $\sum_{j=1}^{n} w_{ij} = 1$.

Table 8: Grey Relational Grades

Expt No.	MRR(mg/min)	R_a(μm)	Coeff of MRR(mg/min)	Coeff of R_a(μm)	Grey Relational Grades	Order
1	1	0.137285	0.333333	0.784578	0.55896	11
2	0.985863	0.124805	0.336505	0.80025	0.56838	8
3	0.997396	0.152886	0.333913	0.76583	0.54987	12
4	0.985863	0.124805	0.336505	0.80025	0.56838	8
5	0.231027	0.854914	0.683969	0.369027	0.5265	13
6	0.189732	1	0.724919	0.333333	0.52913	11
7	0.231771	0.9922	0.683274	0.335076	0.50918	12
8	0.15625	0.843994	0.761905	0.372025	0.56697	9
9	0.957589	0.137285	0.343032	0.784578	0.56381	10
10	0.949777	0	0.344881	1	0.67244	3
11	0.956473	0.432137	0.343295	0.536402	0.43985	14
12	0.949777	0	0.344881	1	0.67244	3
13	0.104539	0.648986	0.827076	0.435166	0.63112	5
14	0	0.589704	1	0.45884	0.72942	1
15	0.10119	0.589704	0.831684	0.45884	0.63112	4
16	0.00744	0.589704	0.985338	0.45884	0.72209	2
17	0.901042	0.677067	0.356877	0.424785	0.39083	17
18	0.808036	0.875195	0.382252	0.363585	0.37292	25
19	0.844494	0.728549	0.371887	0.406984	0.38944	19
20	0.804315	0.789392	0.383343	0.38778	0.38556	21
21	1	0.071763	0.333333	0.874488	0.60391	6
22	0.145089	0.725429	0.775087	0.40802	0.59155	7
23	0.844494	0.853354	0.371887	0.369452	0.37067	26
24	0.804315	0.536661	0.383343	0.482318	0.43283	15
25	0.845238	0.787832	0.371681	0.388249	0.37997	22
26	0.815476	0.851794	0.380091	0.369879	0.37499	24
27	0.809524	0.851794	0.381818	0.369879	0.37585	23
28	0.805432	0.75663	0.383015	0.39789	0.39045	18
29	0.819568	0.75039	0.378912	0.399875	0.38939	20
30	0.807664	0.723869	0.382361	0.40854	0.39545	16

Table 9: Average and Range of Grey Relational Grade

Parameters	Average Grey Relational Grade			Max-Min (Range)
	Level 1	Level 2	Level 3	
Pulse on time,T_{on} (μm)	0.533471	0.423338	0.600239	0.176901
Duty cycle DC	0.574356	0.422401	0.560607	0.151955
Peak current I_p (A)	0.57756	0.38736	0.60412	0.21676
Concentration D (g/l)	0.52756	0.420026	0.610569	0.190543
Mean Value of the Grey Relational Grade = 0.18404.				

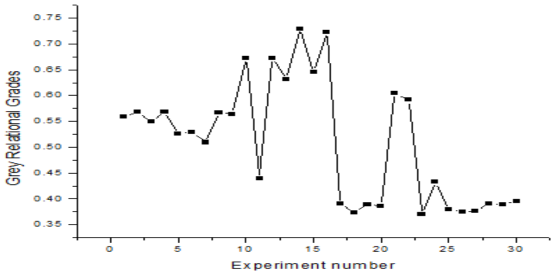


Figure 2: Plot of Experiment Number vs Grey Relational Grades

The above graph is plotted with software Origin The experiment which has highest grey relational grade is said to be best choice of all the runs. Table 12 shows that experiment number 14 is the best run. The optimized process parameters are 150µs/0.7DC/12A/2g/l. I_p was found to be the most influencing factor followed by conc D and then $T_{on,}$ and finally and the least influencing factor DC.

TOPSIS Method

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is one of the many multi criteria decision making method(MCDM) and was firstly proposed by **Hwang and Yoon [10]**. The basic concept of this method is that the chosen alternative (appropriate alternative) should have the shortest distance from the positive ideal solution and the farthest distance from negative ideal solution. Positive ideal solution is a solution that maximizes the benefit criteria and minimizes adverse criteria, whereas the negative ideal solution minimizes the benefit criteria and maximizes the adverse or cost criteria.

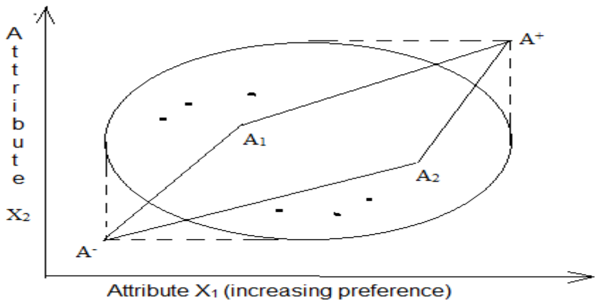


Figure 3: Topsis Graph [10]

The experimental data used in present study is based on the research done by H.K. Kansal, Sehijpal Singh, P. Kumar **[6].**

STEPS FOR TOPSIS

Step 1: Decision Matrix

The first step is to formulate decision matrix with ‘m’ alternatives and ‘n’ attributes **[11].** In this case study there are 30 number of experiments (alternatives) and two output responses MRR and Ra (attributes). Hence the decision matrix is of the order 30 X 2.

$$
D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array}
\begin{array}{c}
\begin{array}{ccccc} X_1 & X_2 & X_3 & \cdots & X_n \end{array} \\
\left[\begin{array}{ccccc}
X_{11} & X_{12} & X_{13} & \cdots & X_{1n} \\
X_{21} & X_{22} & X_{23} & \cdots & X_{2n} \\
\vdots & \vdots & \vdots & & \vdots \\
X_{m1} & X_{m2} & X_{m3} & \cdots & X_{mn}
\end{array}\right]
\end{array}
$$

Figure 4: Decision Matrix

Table 10: Decision Matrix with 30 Alternative and 3 Attributes

Expt No.	MRR(mm^3/min) x_{ij}	Ra(µm) x_{ij}
1	2.03	2.22
2	2.41	2.14
3	2.10	2.32
4	2.41	2.14
5	22.70	6.82
6	23.81	7.75
7	22.68	7.70
8	24.71	6.75
9	3.17	2.22
10	3.38	1.34
11	3.20	4.11
12	3.38	1.34
13	26.10	5.50
14	28.91	5.12
15	26.19	5.12
16	28.71	5.12
17	4.69	5.68
18	7.19	6.95
19	6.21	6.01
20	7.29	6.40
21	2.03	1.80
22	25.01	5.99
23	6.21	6.81
24	7.29	4.78
25	6.19	6.39
26	6.99	6.80
27	7.15	6.80
28	7.26	6.19
29	6.88	6.15
30	7.20	5.98

Step 2: Normalization Matrix

Normalization matrix is formed in order to transform the various attribute dimensions into non-dimensional attributes, which allows comparison across the attributes [11-13]. It is found out by using the following equation.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad .(5)$$

Table 11: Normalized Matrix

Expt No.	MRR(mm³/min) x_{ij}	Ra(μm) x_{ij}
1	2.03	2.22
2	2.41	2.14
3	2.10	2.32
4	2.41	2.14
5	22.70	6.82
6	23.81	7.75
7	22.68	7.70
8	24.71	6.75
9	3.17	2.22
10	3.38	1.34
11	3.20	4.11
12	3.38	1.34
13	26.10	5.50
14	28.91	5.12
15	26.19	5.12
16	28.71	5.12
17	4.69	5.68
18	7.19	6.95
19	6.21	6.01
20	7.29	6.40
21	2.03	1.80
22	25.01	5.99
23	6.21	6.81
24	7.29	4.78
25	6.19	6.39
26	6.99	6.80
27	7.15	6.80
28	7.26	6.19
29	6.88	6.15
30	7.20	5.98

Step 3: Weighted Normalized Decision-Making Matrix

Multiply each column (r_{ij}) by weights 'w_j' assigned to attributes to get V_{ij} [84-87].

$V_{ij}. = w_j * r_{ij}$

In this case equal weights are given to both attributes MRR and R_a.

Table 12: Weighted Normalized Matrix

Weights (w_j)	0.5	0.5
Expt No	MRR(mm³/min) v_{ij}	Ra(μm) v_{ij}
1	0.012615	0.037495
2	0.014976	0.036144
3	0.013049	0.039184
4	0.014976	0.036144
5	0.141056	0.115187
6	0.147954	0.130894
7	0.140932	0.13005
8	0.153546	0.114005
9	0.019698	0.037495
10	0.021003	0.022632
11	0.019885	0.069416
12	0.021003	0.022632
13	0.162184	0.092893
14	0.179645	0.086475
15	0.162743	0.086475
16	0.178402	0.086475
17	0.029144	0.095933
18	0.044678	0.117383
19	0.038589	0.101506
20	0.0453	0.108093
21	0.012615	0.030401
22	0.15541	0.101169
23	0.038589	0.115018
24	0.0453	0.080732
25	0.038464	0.107924
26	0.043436	0.114849
27	0.04443	0.114849
28	0.045113	0.104547
29	0.042752	0.103871
30	0.04474	0.101

Step 4: Determine Ideal and Negative Ideal Solution

Ideal solution;

A^{+} = {(max V_{ij} j Є J), (min V_{ij} j Є **J**) i = 1, 2, 3,……….m}[84-87] (6)

Negative ideal solution;

A^{-} = {(min V_{ij} j Є J), (max V_{ij} j Є **J**) i = 1, 2, 3,……….m} (7)

where;

J = {j = 1, 2, 3, ………n; j associated with benefit criteria}

J = {j = 1, 2, 3, ………n; j associated with cost criteria}

In this case;

Benefit criteria: MRR.

Cost criteria: Ra.

From weighted normalized decision-making matrix, ideal solution A*,

A^{+} = (0.179645; 0.022632)

From weighted normalized decision-making matrix, negative ideal solution A^{-},

A^{-} = (0.012615; 0.130894).

Step 5: Determine Separation from Ideal Solution

The separation measure Si* i.e. the distance of each v_{ij} from ideal solution;

A^{+} =(0.179645; 0.022632). is calculated by using the following equation [12].

$Si^{*} = [\ \Sigma\ (vj^{*}- v_{ij})^{2}\ ]^{½}$ for each row j (8)

Table 13: Separation Measure from Ideal Solution Matrix

Expt No.	Si*
1	0.16769
2	0.165223
3	0.167416
4	0.165223
5	0.100277
6	0.112805
7	0.114181
8	0.095027
9	0.160636
10	0.158642
11	0.16647
12	0.158642
13	0.072398
14	0.063843
15	0.066042
16	0.063855
17	0.167403
18	0.164905
19	0.161611
20	0.159224
21	0.167211
22	0.082191
23	0.168618
24	0.146371
25	0.164945
26	0.16449
27	0.163668
28	0.157508
29	0.159184
30	0.156015

Step 6: Determine Separation From Negative Ideal Solution

The separation measure Si^- i.e. the distance of each v_{ij} from negative ideal solution;A- = (0.012615; 0.130894), is calculated by using the following equation [11,12].

$$Si- = [\ \Sigma\ (v_j - v_{ij})^2\ ]^{½}\ (9)$$

Table 14: Separation Measure from Negative Ideal Solution Matrix

Expt No.	Si^-
1	0.093399
2	0.09478
3	0.091711
4	0.09478
5	0.129398
6	0.135339
7	0.128319
8	0.141939
9	0.093667
10	0.108586
11	0.061906
12	0.108586
13	0.154321
14	0.172835
15	0.156561
16	0.171634
17	0.038672
18	0.034794
19	0.039221
20	0.039852
21	0.100493
22	0.145856
23	0.030441
24	0.059871
25	0.03458
26	0.034747
27	0.035632
28	0.041837
29	0.040478
30	0.043883

Step 7: Relative Closeness Coefficient

The relative closeness/closeness coefficient (C_i*) to the ideal solution is then calculated with the help of following equation [12-13].

$C_i^* = Si-/\ (Si^* + Si-);\ 0< Ci<1;\ i= 1, 2, 3……..m.$

$C_i^* = 1;$ if $A_i = A^+$

$C_i^* = 0;$ if $A_i = A^-$

Table 15: Relative Closeness Coefficient Matrix

Expt No.	C_i*
1	0.357728
2	0.364534
3	0.353923
4	0.364534
5	0.563396
6	0.545404
7	0.529152
8	0.598986
9	0.368329
10	0.406343
11	0.271072
12	0.406343
13	0.680671
14	0.730255
15	0.703319
16	0.728842
17	0.187659
18	0.17423
19	0.195292
20	0.200184
21	0.375388
22	0.639588
23	0.152925
24	0.290295
25	0.173313
26	0.1744
27	0.178784
28	0.209871
29	0.202735
30	0.219526

Step 8: Average Closeness Coefficient

Average closeness coefficient is the weighted sum of the closeness coefficients for a particular experiment and it is calculated using equation (5) [11-13].

$C^0(x_0, x_i) = \sum_{j=1}^{n} w_j \cdot \gamma(x_{0j}, x_{ij})$ for $i = 1,2,3,...,m$ and $j = 1,2,3,....,n$ ………(10)

where, $C(x_0, x_i)$ is average closeness coefficient between comparability sequence X_i and reference sequence x_0 and $\sum_{j=1}^{n} w_{ij} = 1$.

The experiment which has highest relative closeness is said to be best choice of all the runs. The values of average closeness coefficients and range are shown in Table 16.

Table 16: Average and Range of Relative Closeness Coefficients

Parameters	Average Relative Closeness Coefficients			Max-Min (Range)
	Level 1	Level 2	Level 3	
Pulse on time,Ton (µm)	0.446138778	0.251025083	0.479941222	0.228916139
Duty cycle DC	0.467994667	0.467994667	0.461817222	0.006177445
Peak current Ip (A)	0.363132667	0.196601167	0.635512556	0.438911389
Concentration D (g/l)	0.425620222	0.2442475	0.509496556	0.265249056
Mean Value of the relative closeness coefficients = 0.288211271.				

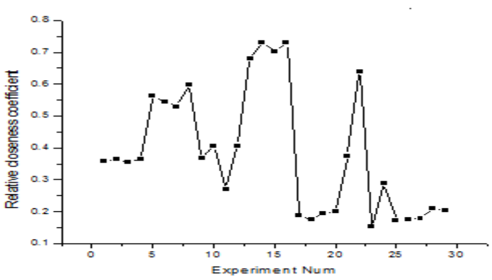
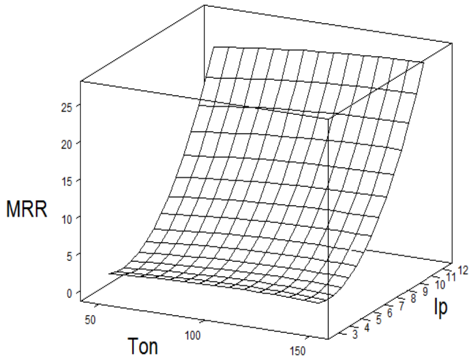


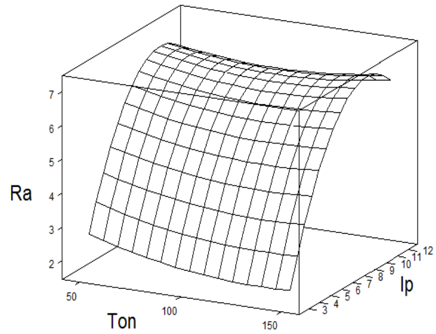
Figure 5: Plot of Experiment Number vs Relative Closeness Coefficient

The above graph is plotted with software Origin.

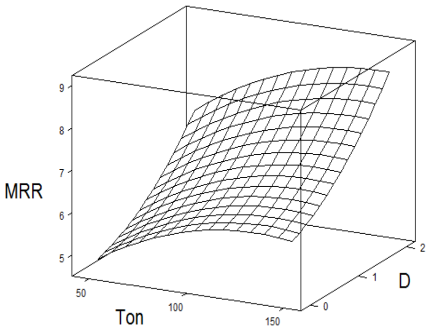
By using Topsis, it was found that the experiment number 14 has the maximum value of grey relational coefficient, which is the best run. The optimized process parameters i.e. pulse-on-time T_{on}, duty cycle DC, peak current I_p, and concentration D were found to be 150µs/0.7DC/12A/2g/l respectively. Peak current I_p was found to be the most influencing parameter followed by concentration D, and then pulse-on-time T_{on}, and finally and the least influencing factor duty cycle DC.



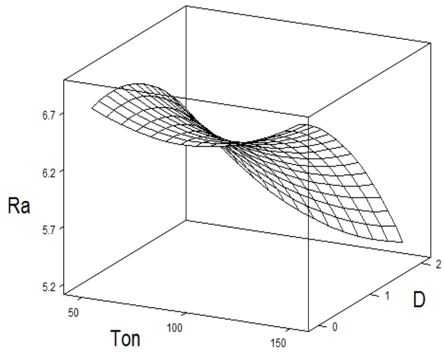
(a) Effect of T_{on} and I_p on MRR



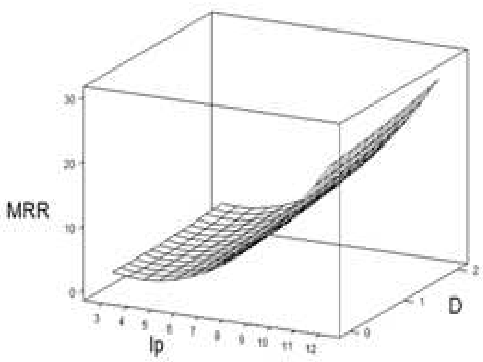
(d) Effect of T_{on} and I_p on R_a



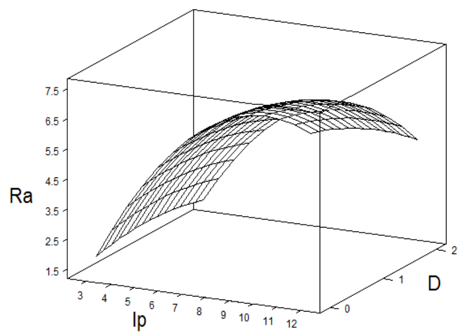
(b) Effect of T_{on} and D on MRR



(e) Effect of T_{on} and D on R_a



(c) Effect of I_p and D on MRR



(f) Effect of I_p and D on R_a

Figure 6: Surface Plots of Various Process Parameters vs Output Responses

RESULTS AND DISCUSSIONS

By using GRA, it was found that the experiment number 14 has the maximum value of grey relational coefficient, which is the best run as shown in Table 8. The optimized process parameters were found to be 150µs/0.7DC/12A/2g/l respectively. I_p,was found to be the most influencing factor since it has the maximum value of range of average grey relational grades as shown in Table 15, followed by conc D and then $T_{on,}$ and finally the least influencing factor DC.

$I_p > D > T_{on} > DC$

With Topsis, experiment number 14 was found to be the optimum run. The optimized parameters were found to be 150µs/0.7DC/12A/2g/l. I_p was found to be the most influencing parameter followed by conc D, and then T_{on}, and finally and the least influencing factor duty cycle DC.

$I_p > D > T_{on} > DC$

Analysis of Material Removal Rate

It was observed that MRR increased with increase of pulse-on-time and peak current. Surface plot indicates that maximum MRR is achieved at 12 A and 150 µs. At low value of pulse-on-time T_{on}, high MRR is achieved at high value of peak current I_p (12A). When silicon powder was suspended into the dielectric fluid of EDM, an enhanced rate of material removal rate was achieved. This is due to the fact that suspended powder causes *bridging effect* between both the electrodes, facilitates the dispersion of discharge into several increments and hence increases the MRR. Maximum MRR is achieved with 2g/l concentration of powder. Hence more improvement in MRR is expected at still higher concentration level of silicon powder. At low concentration higher MRR is achieved at high peak current I_p i.e. 12 A.

Analysis of Surface Roughness R_a

It was observed that surface roughness, R_a increases with increase of pulse-on-time T_{on} and peak current I_p. This is due to their dominant control over the input energy. Surface plot showsminimumR_a is achieved at T_{on} 150µs and I_p 3 A At high values of T_{on} minimum R_a is achieved at low value peak current. Addition of silicon powder into the dielectric fluid improved surface finish of the workpiece. Minimum surface roughness is achieved at high concentration 2g/l. Hence surface roughness is expected to be less with increasing concentration of silicon powder.

CONCLUSIONS

This study yielded the following conclusions.

- MRR and surface roughness R_a increases with increase of pulse-on-time T_{on}, and peak current $I_{p.}$
- An enhanced rate of material removal was achieved when powder abrasives i.e. silicon powder was suspended into the dielectric fluid.
- Surface roughness R_a improves with addition of silicon powder and is expected to improve more with more concentration of powder.
- GRA and Topsis yielded the same optimum experiment run i.e. 14. The optimized process parameters are.150µs/0.7DC/12A/2g/l.
- With both GRA and Topsis, peak current I_p was found to be the most influencing parameter followed by concentration D, and then pulse-on-time $T_{on,}$ and finally and the least influencing factor duty cycle DC.

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